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Palm Vein Detection Based on Local Gabor Vein Code Pattern and Hog

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Abstract: ***Nowadays, Palm vein biometric is one of the emerging techniques to build up a well-organized recognition system. This paper focuses on quality-based palm vein detection. To recognize hand palm vein images, Local Gabor Vein Code Pattern (LGVCP) is proposed. It comprises of three modules, namely Preprocessing, LGVCP and Palm Vein matching. Preprocessing is performed using Otsu thresholding method and Contrast Limited Adaptive Histogram Equalization (CLAHE) techniques. Palm vein features are extracted by applying LGVCP and Histogram of Oriented Gradients (HOG). Chi-square distance and Euclidian distance values are applied for palm vein matching. Experiments are performed on CASIA Palm vein Image database. The performance of the proposed method is evaluated by metrics, namely accuracy, specificity, sensitivity, error rate, recall and precision. The proposed method provides an accuracy of 99.001% compared to the existing ones.***

Keywords **: Palm Vein, OTSU, LGVCP, ROI,CLAHE,HOG**

I. INTRODUCTION

"Biometric" is one of the automatic methods to identify the physical characteristics of a human being digitally. Some familiar practical examples are fingerprint, face, iris, hand geometry, voice and dynamic signature. The Digital Identification methods are preferred over traditional methods involving passwords and PIN numbers for various reasons: (i) The physical presence of the person to be recognized is mandatory (ii) biometric identification eliminates remembrance of the password [3].

In [1, 2] Young and Chen have presented concept of palm print recognition based on the texture information of vein blood vessel under the palm skin layer.

The following steps are followed 1. Extract ROI of palm vein image 2. LGVCP and HOG for feature extraction 3. Calculate the distance for computing the matching score.

The remaining of this paper is organized as follows. Section 2 briefly summarizes related work. Section 3 describes the methodology applied in the paper. Section 4 discusses metrics used for the performance evaluation. Section 5 discusses experimental results. Section 6 provide to conclusions

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II. RELATED WORK

Pawan Dubey et.al [4] have presented a novel Palmprint recognition scheme by applying Anisotropic Filters (AFs) which outweighs the Gabor Filters. Gabor Filters although used extensively are inefficient for image recognition under varying illuminations, possess high complexity and have large storage requirement. The Anisotropic Filters were applied optimally followed by Local Binary Pattern (LBP) known as Optimal Local Direction Binary Patterns (OLdirBP) for feature size reduction. Thus a Palmprint recognition system was proposed with low computational complexity, small features length and robust to noise.

Gaurav Jaswal et.al [5] have presented a texture based Palmprint recognition method. To extract texture information from the palm and use subspace methods for dimension reduction. The test and training images were compared in terms of calculating Euclidean distance between them. The proposed algorithm was tested on standard databases (CASIA and IIT Delhi) and the results highlight on the accuracy of proposed method in terms of the Correct Recognition Rate and Computation Time.

Cancian et.al [6] have presented an Embedded Gabor-based Palm Vein Recognition System which described the development of an embedded standalone palm vein authentication system. Image is captured for contact-less acquisition on the key points is isolated by Hand tracking algorithm. Then the image is enhanced by CLAHE preprocessing and the feature is extracted through multiple Gabor filters and the modules are matched. Thus the user can be identified or authenticated by the resultant vector.

J.C. Lee [7] has discovered texture descriptors Local Binary Patterns (LBP) and Uniform Local Binary Patterns (LBPU). Extract methods for biometric verification, which employ hand segmentation, Meaningful point detection and ROI detection and enhancement to preprocess the image. Then the biometric features are represented by Texture description and it is tested by Uniform Binary Patterns and LBP are compared

Leila Mirmohamadsadeghi et.al [8] have presented texture based palm vein recognition which employs two operators. There are local binary pattern (LBP) operators as well as the local derivative pattern (LDP) operators, that were brought into a comparison and LBP is observed to be the proficient descriptors for palm vein recognition. Then palm vein recognition is investigated by LDP histograms. Finally the framework of detection and verification are compared along with the evaluation of both the feature extraction methods.

Yingbo Zhou et.al [9] have presented human identification using palm-vein images to decide the identity which employs preprocessing, feature extraction and module matching which is finally compared to database.

Wenxiong Kang [10] has presented Contactless Palm Vein Recognition Using a Mutual Foreground-Based Local Binary Pattern which employs MPC and K means method for texture extraction. Then LBP matching strategy between gray scale images. The best matching region is obtained by MPR and the matching score is obtained. Finally the computational efficiency is increased.

III. METHODOLOGY

The proposed work has three modules as shown in the Fig 1.

1. Image Preprocessing
2. Feature Extraction using LGVCP
3. Palm Vein Matching

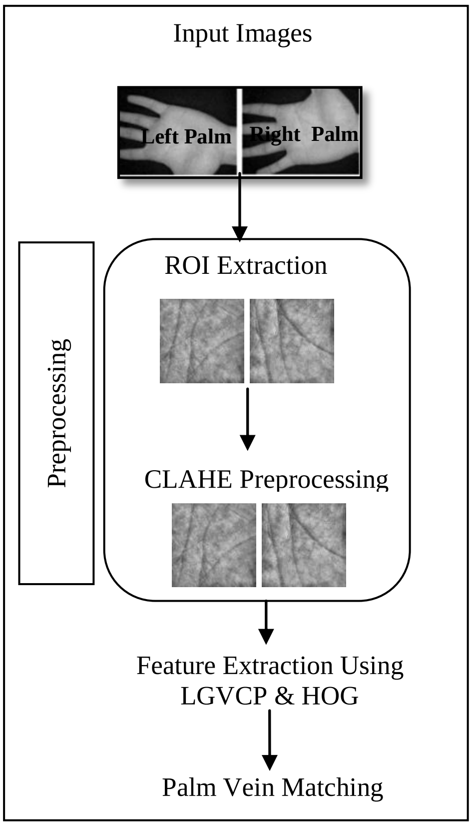


Fig 1. Modules of Palm Vein Detection

3.1 Image Preprocessing

For preprocessing, images of CASIA MS Palm Print database are used. The database has the sample palm print images of both left and right hands. The Region of interest values is extracted from the image and then they are examined.

The steps involved in extracting the region of interest values are:

1. Gaussian filter is used to remove the undesirable noises present in the image.
2. Ots'u threshold algorithm is used to convert gray scale image to binary image.
3. Determine two important reference points and rotate image.
4. Draw rectangle or square around the region of interest (ROI).

3.1.1. OTSU

Otsu method is used to estimate the threshold value. The threshold value is calculated by subtracting the sum of foreground and background pixels where the pixel values are minimum. In [11], Otsu thresholding method was used to convert the original image to binary image so that the hand image is segmented. The OTSU algorithm [13] is subsequently applied to obtain the initial threshold Th, which can be used to segment hand shape after multiplied by an adjustment coefficient C to obtain the new threshold Th.

3.1.2. Normalization Size (Dimension)

Normalization of ROI image size is the process of resizing the image of ROI to the least size of all images of ROI palms used in the system. ROI image normalization size used was 256 x 256 pixels.

3.1.3. Contrast Enhancement using CLAHE

CLAHE preprocessing method is applied to enhance the contrast of gray scale images. In this preprocessing, the parameter values such as Distribution and Rayleigh are used. Distribution parameter means that desired histogram shape and Rayleigh parameter is used to create a bell shaped histogram.

3.2 Feature Extraction using LGVCP

3.2.1. Gabor Filter

Gabor filters are band pass filters. They are used in image processing for feature extraction. Gabor filter performs Gabor transform which can be changed within small period of time with Gaussian window for the classification of area of space. Blending information of content that adjust the image shorthand which combine the appearance of information of an image. By fixing there causes the variation in appearance of an image. This difference in form can be featured by Gabor output gained by 2D Gabor filtering [16].The two dimensional Gabor filter describe the information of appearance because of its space selectivity and location [15]. Gabor filters here asked for an alert in biometrics research humans mainly due to its vicinity decision, spatial allocation and spatial frequency characterization.

2D Gaussian functions as expressed as refer (1) and (2).

$$G_{\sigma,\mu,\theta}\,(x,y) = g_\sigma(x,y).exp\{2\,\pi i\mu\,(x\cos\theta + \mathrm{y}\sin\theta)\} \quad (1)$$

Where i $=\sqrt{-1}$ and $g_\sigma(x,y)$ is a Gaussian envelope defined as

$$g_\sigma(x,y) = \frac{1}{2\pi\sigma^2}\,.\exp\left\{\frac{-(x^2+y^2)}{2\sigma^2}\right\} \qquad (2)$$

where $\sigma -$ Standard deviation sigma of Gaussian factor.
$\theta -$ Orientation of the normal to the parallel stripes.
$\mu -$ Frequency.

$G_{\sigma,\mu,\theta}\,(x,y)$ term can be decomposed into a real part ($VR_{\sigma,\mu,\theta}\,(x,y)$)and imaginary part ($VI_{\sigma,\mu,\theta}\,(x,y)$) by using Euler's Formula as shown in (3) - (5).

In palm vein image, for ridge detection is used the real part and the edge detection is used the imaginary part.

$$G_{\sigma,\mu,\theta}\ (x,y) = VR_{\sigma,\mu,\theta}(x,y) + i.VI_{\sigma,\mu,\theta}(x,y) \qquad (3)$$

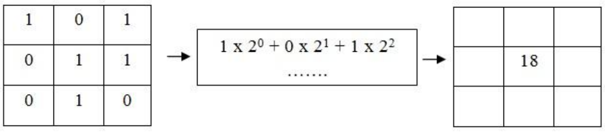
$$VR_{\sigma,\mu,\theta}\ (x,y) = g_{\sigma}(x,y).\cos[2\pi\mu\ (x\cos\theta + y\ sin\theta] \quad (4)$$

$$VI_{\sigma,\mu,\theta}\ (x,y) = g_{\sigma}(x,y).\sin[2\pi\mu\ (x\cos\theta + y\ sin\theta] \quad (5)$$

Each sub region was convolute with a 2D Gabor filter until the whole ROI image was traversed [17]. The left and right hand palm features are extracted from the palm vein image and they were then encoded into a binary form VR, VI which is defined in the following equation (6) and (7) respectively:

$$\mathrm{VR} = \begin{cases} 1 & \text{if RegaboutR} \geq 0 \\ 0 & \text{if RegaboutR} < 0 \end{cases} \qquad (6)$$

$$\mathrm{VI} = \begin{cases} 1 & \text{if ImgaboutR} \geq 0 \\ 0 & \text{if ImgaboutR} < 0 \end{cases} \qquad (7)$$



3.2.2 Proposed LGVCP

The original LGVCP operator assigns some decimal numbers to the pixels of an image. These decimal numbers are called as Local Gabor Vein Code Patterns or LGVCP codes. The LGVCP code is used to encode the local structure around each pixel. It proceeds thus, as illustrated in Fig.2:

Fig 2: Real & Imaginary Values Conversion Equation Decimal values (Binary Number)

3.2.3 LGVCP Algorithm

- The palm vein image which is in grayscale format has Real and Imaginary values (Binary Values).
- A binary number is obtained by concatenating all the binary codes in a clock wise direction starting from the top-left one and its corresponding decimal value is used for labeling.
- Then, we convert this binary value to a decimal value using (3).

$$1\ \times 2^0\ +\ 0\ \times 2^1\ +\ 1\ \times 2^{\,1}\ \ldots.. \quad (3)$$

- LGVCP procedure gives us a new image which represents better the characteristics of the original image.
- Histogram made by using LGVCP feature vector values.

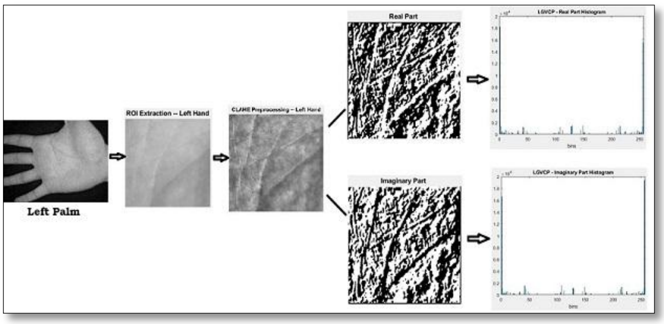


Fig 3. LGVCP Histogram

3.2.4 Histogram of Oriented Gradients (HOG)

The most commonly used descriptor is the Histogram of Oriented Gradients (HOG), which is used for facial detection and object recognition. It provides high performance under different conditions [18].
The HOG method extracts information from the target edges in the local regions as a means of representing the target shape [18, 21]. The HOG method calculates characterization of the orientation (θ) and magnitude (m) values of the pixels within the image. The main reason of this approach is to define an image as a group of local histograms [19]. At first, the HOG splits the image into several cells, then for each cell, the gradient direction histogram is calculated. Finally, the descriptor is built with the help of combining those histograms [20].

The following steps are used for calculating HOG feature descriptor.

- Calculate the vertical and Horizontal gradients for each pixel.

$$\mathrm{HX} = [-1\ \ 0\ \ 1\ ],\ \mathrm{HY} = [-1\ \ 0\ \ 1]\ \mathrm{T} \qquad (8)$$

- Apply multidimensional filtering using Convolution [14].
- To calculate the magnitude and gradient values by using equation (9, 10).

$$\mathrm{m} = \sqrt{\mathrm{grade}_x^2 + \mathrm{grade}_y^2} \qquad (9)$$

$$\theta = \arctan\frac{\mathrm{grade}_x}{\mathrm{grade}_y} \qquad (10)$$

Where,
m - Magnitude value
θ - Direction of gradient

- Create a cell histograms (i.e) 9 bins
- Histogram Normalization

Histogram of Orientation gradient technique used to calculate the Chi-square distance and Euclidian distance

3.3 Palm Vein Matching

In this module, a new algorithm for palm vein matching is introduced.

Algorithm

Input : An image from CASIA MSPALM PRINT
Output : The feature vector of all the sample images are extracted
1 Choose an Image from CASIA MS PALMPRINT Database.
2 ROI Extraction using OTSU technique is applied.
3 CLAHE Preprocessing is applied
4 Extract the feature values using the Local Gabor Vein Code Pattern and HOG.
5 Calculate the Chi-square distance and Euclidian distance for Palm vein matching using the following Equations 14 & 15.

$$x^2(x_i, x_j) = \frac{1}{2}\sum_{l=1}^{d}\frac{(x_{il} - x_{jl})^2}{x_{il} + x_{jl}} \quad (14)$$

$$Ed = \sqrt{\sum_{i=1}^{n}(x_i - x_j\ )^2} \quad (15)$$

6 Results are estimated

3.4. Database Description

The CASIA Multi-Spectral Palm print Image Database V1.0 [12], collected by the Chinese Academy of Sciences Institute of Automation (CASIA), has been used for evaluation purposes. It contains 5,502 palmprint images captured from 312 subjects. For each subject palmprint images from both left and right palms are collected. In this Database one subject contains 8 left and 8 right possible palm vein images.

IV. PERFORMANCE EVALUATION

Table 4.1 represents the confusion matrix of the proposed system. In this table, the row indicates the predicted class and the column indicates the actual class. From this confusion matrix, t_{po} and t_{ne} indicate the number of positive and negative instances that are correctly classified. Meanwhile, f_{po} and f_{ne} indicate the number of misclassified negative and positive instances, respectively.

Table 4.1. Confusion Matrix for Binary Classification

Actual Positive Result	Actual Negative Result
True positive (t_{po})	False negative(f_{ne})
False positive (f_{po})	True negative (t_{ne})

The performance of the classifier is evaluated with the different values derived from Accuarcy, Sensitivity, Error Rate, Specificity, Recall, Precision and so on. Table 4.2 shows the metrics with formula.

Table 4.2. Metrics

METRICS	FORMULA	EVALUATION FOCUS
Accuracy(acc)	$\frac{t_{po} + t_{ne}}{t_{po} + f_{po} + t_{ne} + f_{ne}}$	It measures the ratio of accurate predictions over the total range of times evaluated.
Error Rate (err)	$\frac{f_{po} + f_{ne}}{t_{po} + f_{po} + t_{ne} + f_{ne}}$	It measures the ratio of wrong predictions over the whole variety of times evaluated.
Sensitivity (sn)	$\frac{t_{po}}{t_{po} + f_{ne}}$	It measures the fraction of positive patterns that are classified
Specificity (sp)	$\frac{t_{ne}}{t_{ne} + f_{po}}$	It measures the fraction of negative patterns that are classified
Precision (p)	$\frac{t_{po}}{t_{po} + f_{po}}$	It measures the positive patterns which might be efficaciously anticipated from the overall anticipated styles in a positive class.
Recall (r)	$\frac{t_{po}}{t_{po} + t_{ne}}$	It measures the fraction of positive patterns which can be effectively classified
F-Measure (FM)	$\frac{2*p*r}{p+r}$	It represents the harmonic mean between recall and precision values.

V. EXPERIMENTAL RESULTS

Accuracy, Sensitivity, Precision, Recall, F-Measure for both left and right palm images are compared. In Table 5.1 indicates values of the accuracy, specificity, precision of both the palm images which are equal for Chi-Square distance. The values of Sensitivity, Recall and F-Measure of both the palm images are exceptional for Chi-Square distance.

Table 5.1: Performance of LGVCP With Chi-Square Distance

Measures	LEFT PALM	RIGHT PALM
Accuracy	98.57	98.58
Sensitivity	75.59	76.96
Specificity	98.64	98.65
Precision	77.82	78.64
Recall	75.59	76.96
-Measure	75.51	76.61

In Table 5.2, suggests the performance comparison between the Chi-Square distance and Euclidian distance. The values of accuracy and specificity of both the palm images which are same for Chi-Square distance and Euclidian distance. The values of Sensitivity, Precision , Recall and F-Measure of both the palm images are one of a kind for Chi-Square distance and Euclidian distance.
From Table 5.3, on comparing with the existing technique, the proposed method provides better accuracy. The proposed approach has a lesser error rate in comparison to existing method. And then the error rate has shown in fig 5.

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Table 5.3: Comparison of Various Methods Accuracy & Error Rate

METHOD	ACCURACY %	ERROR RATE
LBP [22]	87.5	0.125
MF – LBP [22]	92.5	0.075
LDTP [22]	92.5	0.075
MF – LDTP [22]	95	0.05
HOG [17]	98.66	0.0134
LGVCP	98.581	0.0142
LGVCP + HOG	99.001	0.0099

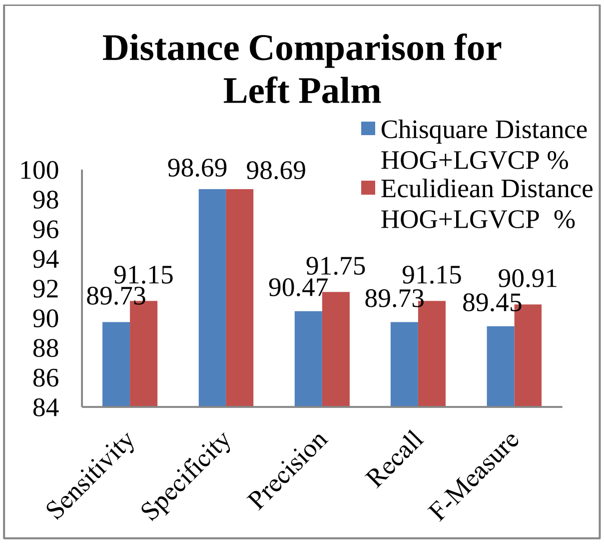

Fig 4: Comparison For Left Palm Distance

Fig 4 shows the comparison between Chi-square distance and Euclidean distance for Left palm. According to the comparison Euclidean distance is best. The performance of the left palm is listed in Table 5.2.

Table 5.2: Comparison Between Chi-square And Euclidian Distance

	LEFT PALM				RIGHT PALM			
	Chisquare Distance		Euclidian Distance		Chi-square Distance		Euclidian Distance	
METHOD	HOG %	LGVCP + HOG %	HOG %	LGVCP+ HOG %	HOG %	LGVCP + HOG %	HOG %	LGVCP + HOG %
Accuracy	98.66	99.00	98.66	99.001	98.66	99.00	98.66	99.001
Sensitivity	89.81	89.73	89.56	91.15	89.55	89.80	89.37	90.04
Specificity	98.69	98.69	98.69	98.69	98.69	98.69	98.69	98.69
Precision	90.39	90.47	90.20	91.75	90.39	90.57	90.14	90.74
Recall	89.81	89.73	89.56	91.15	89.55	89.80	89.37	90.04
F-Measure	89.60	89.45	89.34	90.91	89.35	89.52	89.18	89.83

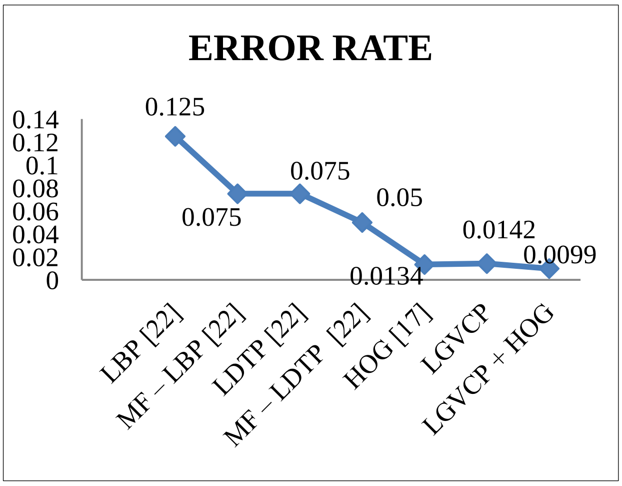

Fig 5: Comparing Various Techniques with Error Rate

Table 5.3 illustrates the accuracy and error rate comparison. In this table, LGVCP + HOG method provide 1% higher accuracy than HOG method. LGVCP + HOG method provide 4% better accuracy than MF LDTP method. LGVCP + HOG method provide 7% higher accuracy than LDTP and MF LBP methods. LGVCP + HOG method provide 12% better accuracy than LBP method. Fig 5 indicates the bar diagram of various methods error rate. According to the diagram LGVCP + HOG method provide lesser error rate comparing to other methods.

VI. CONCLUSION

This paper fully focused on quality-based palm vein detection. Local Gabor Vein Code Pattern (LGVCP) is proposed to recognize hand palm vein images. Palm vein features are extracted by applying LGVCP and Histogram of Oriented Gradients (HOG). The proposed method constitutes local features within the images. It is also robust towards monotonic gray scale transformations. Chi-square distance and Euclidean distance values are applied for palm vein matching. Experiments are performed on CASIA Palm vein Image database. The proposed method provides an accuracy of 99.001% compared to the existing ones.

The combination of LGVCP + HOG method provides 1% higher accuracy than HOG method and 12% better accuracy than LBP method.

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